IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

In Re Application of :

V. Castelli, et al : Group Art No.: 2172

Serial No. 09/237,646 : Examiner: C. Truong

Filed: January 26, 1999 : for IBM Corporation
Anne Vachon Dougherty
3173 Cedar Road
Yorktown Heights, NY 10598

Title: METHOD AND APPARATUS FOR SIMILARITY RETRIEVAL FROM ITERATIVE

DECLARATION OF PRIOR INVENTION IN THE UNITED STATES TO OVERCOME CITED PATENT OR PUBLICATION (37 CFR 1.131)

Commissioner of Patents and Trademarks
Washington, D.C. 20231

Sir:

1. This declaration is to establish completion of the invention in this application in the United States at a date prior to March 16, 1998, which is the earliest effective date of the U. S. Patent No. 6,298,342, of Graefe, et al entitled "Electronic Database Operations For Perspective Transformations on Relational Tables Using Pivot and Unpivot Columns" which was cited by the Examiner in the prosecution of the above-identified patent application.

2. The people making this declaration are Vittorio Castelli, Chung-Sheng Li, and John R. Smith, the original joint inventors, who are the present applicants for the pending patent application.

3. To establish the date of completion of the invention of this application, the following attached document is submitted as evidence:

the invention disclosure submission form.

From this document, it can be seen that the invention in this application was made at least by the date March 16, 1998, which is a date earlier than the effective date of the cited reference.

4. As a person signing below:

I hereby declare that all statements made herein of my own knowledge are true and that all statements made on information and belief are believed to be true; and further that these statements were made with the knowledge that willful false statements and the like so made are punishable by fine or imprisonment, or both, under Section 1001 of Title 18 of the United States Code, and that such willful false statements may jeopardize the validity of the application or any patent issued thereon.

Full name of inventor: Vittorio Castelli

Inventor's signature Vittorio Castelli

Date 2/11/2002 Country of citizenship Italy

Residence 55 North Broadway, #2-17, White Plains, NY 10601

Post Office Address same as above

Full name of inventor: Chung-Sheng Li

Inventor's signature

Date 02/05/2002 Country of citizenship U.S.A.

Residence 50 Croton Ave., Apt. 2C, Ossining, NY 10532

Post Office Address same as above

Full name of inventor: John R. Smith

Inventor's signature John R. Smith

Date 02/05/2002 Country of citizenship U.S.A.

Residence 40 Farrell Street, New Hyde Park, NY 11040

Post Office Address same as above

IBM Confidential

OIPE JC46
FEB 2 1 2002
PATENT & TRADEMARK OFFICE

900

97 DEC 22 AM 11:12

Disclosure No.	FOR USE BY PATENT OPERATIONS Patent Attorney	Where & When Received (Time Stamp)
Y0898-0009		
Evaluator	Functional Code	

Full Name(s) of Inventor(s)	Userid/Node	Emp. Serial	Div/Dept	Bldg/Zip	Location	Tel. Num.
Chung-Sheng Li	csli@watson	397997	22/9AU	790/H2-B52	Hawth.	863-6661
Vittorio Castelli	vittorio@watson	707255	22/9AU	790/H2-J24	Hawth.	863-7665
John R. Smith	jrsmith@watson	994145	22/9AU	790/H2-D25	Hawth.	863-7320

Title of Invention

S-STIR: Similarity Search Through Iterative Refinement

Problem Solved by This Invention (*summary*)

Similarity retrieval of images based on texture and color features has generated a lot of interests recently. Most of these similarity retrievals are based on the computation of the Euclidean distance between the target feature vector and the feature vectors in the database. Euclidean distance, however, does not necessarily reflect either relative similarity required by the user. In this paper, a method based on nonlinear multidimensional scaling is proposed to provide a mechanism for the user to dynamically adjust the similarity measure. The results show that a significant improvement on the precision versus recall curve has been achieved.

BACKGROUND INFORMATION

(a) To what ☑ IBM project, ☐ Proposal, ☐ or Product, ☑ or government contract is this invention related? 500P NCC5-101
(b) Related and background publications: See References
(c) Keywords for database search for related work: Invention Disclosure
(d) Critical Dates:
(e) Suggested TEC: Anant Jhingran

INVENTOR ON INTERNATIONAL ASSIGNMENT: Is any inventor of this disclosure in this country on assignment from another country? ☑ YES, ☐ No. If 'Yes', see Instruction #5.

Problem solved by this invention

Recent methods for retrieving images and videos by content from large archives utilize feature descriptors and feature comparison metrics in order to index the visual information. Examples of such content-based retrieval

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure		DISCLOSURE SUBMITTED BY			
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
[signature]	12/18/97	[signature]	12/18/97		
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
[signature]		[signature]	12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date
		[signature]	12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date

systems include the IBM Query by Image Content (QBIC) system [4], the Virage visual information retrieval system [1], the MIT Photobook [7], the Alexandria project at UCSB [6, 2], and the IBM/NASA Satellite Image Retrieval System [5].

In these systems, the feature comparison between the search target and those feature vectors stored in the database is typically based upon a simple fixed metric, such as the Euclidean distance or the quadratic distance [4, 8]. While these simple metrics may minimize the computational requirements for feature comparison, they typically do not correspond well to human perceptual distance nor do they have the capabilities to adapt to the changing environment commonly arising in various scientific applications:

- Retrieve those Synthetic Aperture Radar (SAR) Satellite images and identify those regions in the images with similar ice type (can be recognized through texture features) to the search target,
- Retrieve those one-meter resolution satellite images and identify those regions in the images with similar crop type (can be recognized through spectral features) to the search target,
- Retrieve those LANDSAT Thematic Mapper (TM) satellite images and identify those regions in the images with similar terrain type (can be recognized through a combination of spectral and texture features) to the search target.

Consequently, each image in the three scenarios described above usually has applications in more than one domains.

In order to improve the results from feature comparison, The VisualSEEk project at Columbia University [8] and the Alexandria project [6, 2] have developed linear transformations of texture feature spaces. Image database allowing relevance feedback has also been investigated previously, for example, in PicHunter [3]. In PicHunter, the history of user selection is used to construct system's estimate of the user's goal image. A Bayesian learning based on probabilistic model of the user behavior is combined with user selection to estimate the probability of each image in the database. All of these methods definitely provide some improvement in image retrieval performance. However, these systems and their use of fixed transforms do not model the user and retrieval process sufficiently. Human perception is highly subjective and dependent on viewing conditions, context, and the corresponding retrieval task. The feature comparison should adapt to these variables.

Description of this invention

In this invention, we disclose an algorithm to enable the revision of feature and metric transformations based upon the interaction with the user in the retrieval process. This algorithm is based upon nonlinear multidimensional scaling (MDS) that refines the feature space based upon the user's evaluation of the retrieval results. In this system, the linear transform of the features is modified by the user's feedback. Furthermore, a deepest gradient decent process is developed to enable fast convergence of the matrix, which makes the method suited to the interactive query environment.

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure		DISCLOSURE SUBMITTED BY			
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
[signature]	12/18/97	[signature]	12/15/97		
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
[signature]		[signature]	12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date
		[signature]	12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date

97 DEC 22 AM 11:12

The organization of this paper is as follows: Section 2 gives a preliminary concept of image and feature database. The proposed algorithm is described in detail in Section 3. Section 4 discusses the implementation and experiments. A brief summary is given in Section 5.

1 Preliminary

We assume that an image database consists of a set of N feature vectors. Each feature vector has n dimensions. The feature vectors potentially represent a combination of color, texture and shape information.

A query is started by presenting a query feature vector to the system. Consider that the feature vector may correspond to a particular query image, region or object. Initially, the K best matches are retrieved using a Euclidean metric. For two n-dimensional feature vectors $\mathbf{u}$ and $\mathbf{v}$, where $\mathbf{u} = [u_1, ..., u_n]^T$ and $\mathbf{v} = [v_1, ..., v_n]^T$, the Euclidean distance between these vectors is defined as:

$$D(\mathbf{u},\mathbf{v}) = \left[(\mathbf{u}-\mathbf{v})^T(\mathbf{u}-\mathbf{v})\right]^{1/2} = \sqrt{\sum_{i=1}^{n}(u_i - v_i)^2} \tag{1}$$

or, in general, the L^p distance metric which is defined as

$$\begin{aligned} D_p(\mathbf{u},\mathbf{v}) &= \left(\sum_{i=1}^{n}|u_i - v_i|^p\right)^{1/p}, \quad \forall p \in [1,\infty), \\ &= \max_i |u_i - v_i|, \qquad \text{for } p = \infty. \end{aligned}$$

The K results whose feature vectors are closest to the target feature vectors are then returned to the user for visual inspection or further processing.

The performance of the retrieval is measured in terms of precision and recall, defined below. Let X be a template, n_X be the number of matches in the database, n_Q be the requested number of results. The query returns $N_C(X, n_Q)$ of the n_X matches, where $N_C(X, n_Q) \leq \min(n_Q, n_X)$. In the following definitions, let n_Q be fixed, and let $\mathbf{E}_X[\cdot]$ denote the expectation with respect to X.

- *Precision*, R_B: This is the proportion that the retrieved results that are relevant. For each template X, define $R_B(X, n_Q) = N_C(X, n_Q)/n_Q$. Then,

$$R_B(n_Q) = \mathbf{E}_X[R_B(X, n_Q)] = \mathbf{E}_X\left[\frac{N_C(X, n_Q)}{n_Q}\right]. \tag{2}$$

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure	DISCLOSURE SUBMITTED BY			
Signature of Witnesses / Date: 12/18/97	Inventor's Signature	Date: 12/15/97	Inventor's Signature	Date
Signature of Witnesses / Date	Inventor's Signature	Date: 12/18/97	Inventor's Signature	Date
	Inventor's Signature	Date: 12/18/97	Inventor's Signature	Date
	Inventor's Signature	Date	Inventor's Signature	Date

- *Recall*, R_A: This is the proportion of the relevant results that are retrieved. For each template X let $R_A(X,n) = N_C(X,n)/\min(n_X,n)$, the proportion of correct results in a retrieved set of size n. Then ,

$$R_A(n_Q) = \mathbf{E}_X[R_A(X,n_Q)] = \mathbf{E}_X\left[\frac{N_C(X,n_Q)}{\min(n_X,n_Q)}\right]. \tag{3}$$

Both $R_B(n_Q)$ and $R_A(n_Q)$ are estimated in the experiments by sample averages, and precision versus recall plots for each template X are obtained by varying n outside the range $[0,n_X]$ where $R_E = R_A$.

2 PROPOSED METHOD

In this section, we will first outline the nonlinear multidimensional scaling technique that is used in the proposed algorithm, and then outline the iterative refinement procedure.

2.1 Nonlinear Multidimensional Scaling

The goal of the iterative refinement process is to discover the best transformation such that the set of vectors in the desired class has minimum separation while the distance between those vectors in different classes is preserved or maximized.

This method is based on the multidimensional scaling method proposed by Webb [9]. The objective is to discover a transformation to transform all of the $\mathbf{x}_i$'s in an n-dimensional vector space $\mathcal{X}$ to $\mathbf{y}_i$'s in an m-dimensional vector space $\mathcal{Y}$:

$$\mathbf{y}_i = \mathbf{W}^*\phi(\mathbf{x}_i) \tag{4}$$

such that the following cost function

$$J = (1-\lambda)J_{se} + \lambda J_{sp} \tag{5}$$

is minimized. In this function, J_{se} is a class separability criterion, and J_{sp} is a structure preserving criterion. where $\mathbf{W}$ is an $l \times m$ matrix, and $\phi(\mathbf{x}_i)$ is a radial basis function where the i^{th} component ($i = 1,..,l$) is defined as

$$\phi_i(\mathbf{x}) = exp\left(-\frac{|\mathbf{x}-\mathbf{c}_i|}{h^2}\right) \tag{6}$$

The parameter h^2 is a *bandwidth* term where larger value gives rise to a smaller bandwidth.

The class separability sums up the intraclass distance for all the pairs of vectors defined as below:

$$J_{se} = \sum_i\sum_j \delta(\omega_i,\omega_j)\alpha_{ij}q_{ij}^2 \tag{7}$$

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure	DISCLOSURE SUBMITTED BY	
Signature of Witnesses — Date 12/18/97	Inventor's Signature — Date 12/18/97	Inventor's Signature — Date
Signature of Witnesses — Date	Inventor's Signature — Date 12/18/97	Inventor's Signature — Date
	Inventor's Signature — Date 12/18/97	Inventor's Signature — Date
	Inventor's Signature — Date	Inventor's Signature — Date

97 DEC 22 AM 11:12

where ω_i and ω_j are the class labels of vector $\mathbf{x}_i$ and $\mathbf{x}_j$, and

$$q_{ij} = |\mathbf{f}(\mathbf{x}_i) - \mathbf{f}(\mathbf{x}_j)| = |\mathbf{W}^*(\phi(\mathbf{x}_i) - \phi(\mathbf{x}_j))|, \tag{8}$$

The function $\delta(\omega_i, \omega_j)$ is defined as below:

$$\delta(\omega_i, \omega_j) = \begin{cases} 1, for & \omega_i = \omega_j \\ 0, for & \omega_i \neq \omega_j, \end{cases} \tag{9}$$

α_{ij}'s are positive weights, defined as

$$\alpha_{ij} = \frac{1/d_{ij}(\mathbf{X})}{\sum_i \sum_j (1/d_{ij}(\mathbf{X}))} \tag{10}$$

where $d_{ij}(\mathbf{X})$ is the Euclidean distance between $\mathbf{x}_i$ and $\mathbf{x}_j$:

$$d_{ij}(\mathbf{X}) = |\mathbf{x}_i - \mathbf{x}_j| \tag{11}$$

The structure preserving criterion is defined as below

$$J_{sp} = \sum_i \sum_j \alpha_{ij} (q_{ij} - d_{ij}(\mathbf{X}))^2 \tag{12}$$

The vectors $\mathbf{c}_i$ can be obtained from applying clustering algorithms such as K-means, Kohonen self-organization map or Tree-Structured Vector Quantizer (TSVQ) to generate l clusters from the dataset. In this paper, TSVQ is assumed due to its relative efficiency and accuracy as compared to other algorithms.

It has been shown [9] that the optimal solution $\mathbf{W}$ to Eq. 5 is the solution to the following equation:

$$\mathbf{AW} = \mathbf{D(V)V} \tag{13}$$

where

$$\mathbf{A} = \sum_i \sum_j \alpha_{ij} [(1-\lambda)\delta(\omega_i, \omega_j) + \lambda](\phi_i - \phi_j)(\phi_i - \phi_j)^* \tag{14}$$

and

$$\mathbf{D(V)} = \sum_i \sum_j c_{ij}(\mathbf{V})(\phi_i - \phi_j)(\phi_i - \phi_j)^* \tag{15}$$

$$c_{ij}(\mathbf{V}) = \begin{cases} \alpha_{ij} d_{ij}(\mathbf{X})/q_{ij}(\mathbf{V}) & (i,j) \in S_+ \\ 0 & (i,j) \in S_0 \end{cases} \tag{16}$$

'97 DEC 22 A11 :12

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure	DISCLOSURE SUBMITTED BY	
Signature of Witnesses / Date: 12/18/97	Inventor's Signature / Date: 12/18/97	Inventor's Signature / Date
	Inventor's Signature / Date: 12/18/97	Inventor's Signature / Date
Signature of Witnesses / Date	Inventor's Signature / Date: 12/18/97	Inventor's Signature / Date
	Inventor's Signature / Date	Inventor's Signature / Date

Note that S_+ correspond to a set consisting of (i,j)'s which result in a $q_{ij}(\mathbf{V})$ greater than zero. On the other hand, S_0 correspond to the set which contains all the (i,j)'s that result in $q_{ij}(\mathbf{V}) = 0$.

The minimization of J will minimize the intraclass distance in the transformed space, while preserving the structure of the feature vectors. In many cases, the structure of individual feature vector can be replaced by the structure of individual cluster. The structure preserving term is essential in this framework. Without this term, a trivial solution $\mathbf{W} = 0$ will be able to minimize J_{se}.

2.2 S-STIR: Similarity Search Through Iterative Refinement

The basic idea of iterative refinement is that the user selects L_1 of the K matches that are most similar to the desired match and reissues the query. Based upon this feedback, the linear or nonlinear transform matrix is modified to better approximate the user's evaluation of similarity. Then, a second set of matches are found and is returned to the user. The user selects the L_2 best matches and again reissues the query. This process is repeated until either the result set converges, or the user stops the process.

If the set of the feature vectors selected by the user up to step $(i-1)$ is denoted as X_{i-1}, then

$$X_i = X_{i-1} \cup U_i \tag{17}$$

where U_i is the set of feature vectors selected during step i.

The vectors that are NOT selected up to step $i-1$ is Y_{i-1}, then

$$Y_i = Y_{i-1} \cup V_i \tag{18}$$

where V_i is the set of feature vectors rejected during step i.

S-STIR Algorithm The proposed algorithm for iterative refinement through nonlinear multidimensional scaling is as follows:

1. Performing similarity search on a feature vector, $\mathbf{v}$, retrieving the K most similar results in the feature space. The similarity between $\mathbf{v}$ and $\mathbf{u}$ is measured by Eq. 1. Set $i = 1$.
2. Initialize X_1 and U_1 to those vectors which are consider to be similar. Also initialize Y_1 and V_1 to those vectors that are not considered to be similar. If the number of vectors is less than a prescribed threshold, set $K = K + K_{inc}$, where K_{inc} is a fixed increment. Return to step 1.
3. Perform the multidimensional scaling described earlier in the previous subsection based on two classes of vectors: X_i and Y_i where X_i include all the vectors that are considered similar, while Y_i include all the vectors that are considered to be no similar (or irrelevant). Consequently, the class label for X_i is 1, while the class label for Y_i is 2. The resulting $\mathbf{W}$ optimize the objective cost function J, as defined in Eq. 5.

4. Perform similarity search in the scaled feature space. The similarity measure between two vectors in the new space is measured by $|W^*(\phi(\mathrm{u}) - \phi(\mathrm{v}))|$. The results are categorized to similar (or relevant) and dissimilar (or irrelevant). Assuming that U_i and V_i are the sets that include those similar and dissimilar vectors, respectively.

5. Update X_i and Y_i as follows

$$X_i = X_{i-1} \cup U_i, \tag{19}$$

$$Y_i = Y_{i-1} \cup V_i. \tag{20}$$

if the difference between X_i and X_{i-1} is less than a prescribed threshold, a equilibrium has been reached and exit.

6. set $i = i + 1$, and return to step 3.

Note that there are a number of possible strategies to handle relevance feedback. The approach described in the algorithm treat all the feature vectors that are relevant equally important. Nevertheless, it is also possible to differentiate vectors during each iteration with different different weights (α_{ij} in Eq. 12 and Eq. 7).

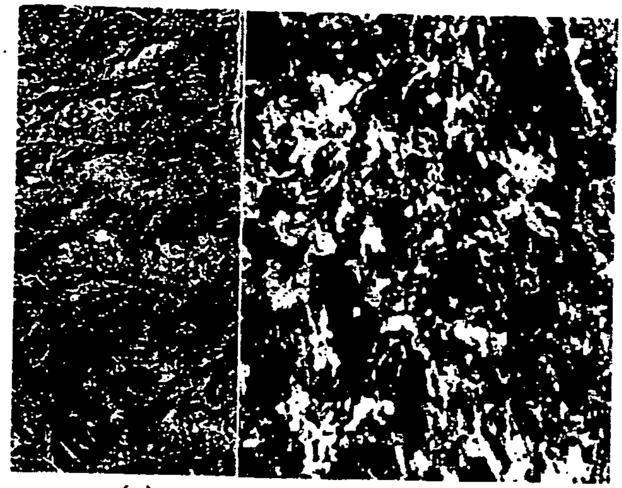
3 IMPLEMENTATION AND EXPERIMENTS

The feature vector used in the database has 21 dimensions, consisting of spatial texture features such as fractal dimension, coocurrence-based texture features, spatial gray level difference-based texture features, coarseness, skew, dispersion, and Moran circular correlation. The feature database is generated as follows: We generate 32 random cuts of size 32×32 from each of the 37 satellite images, each of which consist of homogeneous image regions. A 21-dimensional texture feature is then extracted from each random cut, resulting in a database consisting a total of 1184 feature vectors. For each query, one of the random cuts from an image is used to retrieve the K most similar random cuts. The retrieved result is considered to be a hit if the the retrieved random cut belongs to the same image as the original random cut. Note that the precision and recall values given in this section are all average values, using Eq. 2 and Eq. 3. Figures 3 and 3 show examples of mountain, woods, forests, and suburban areas used in the 37 benchmark images.

To test the algorithm, we retrieve the first K (K varies from 64 to 256) feature vectors as samples and assign class labels. Note that only two feature classes will be covered if K is equal to 64. The iterative refinement algorithm outlined in the previous section is then applied to the retrieved feature vectors together with its feature class. The resulting **W** is applied in conjunction with the radial basis function defined in the previous section to transform all the feature vectors in the database. A nearest neighbor search is then applied to determine the resulting precision and recall values.

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure	DISCLOSURE SUBMITTED BY	
Signature of Witnesses / Date: 12/18/97	Inventor's Signature / Date: 12/18/97	Inventor's Signature / Date
	Inventor's Signature / Date: 12/18/97	Inventor's Signature / Date
Signature of Witnesses / Date	Inventor's Signature / Date: 12/18/97	Inventor's Signature / Date
	Inventor's Signature / Date	Inventor's Signature / Date

DEC 22



(a) (b)

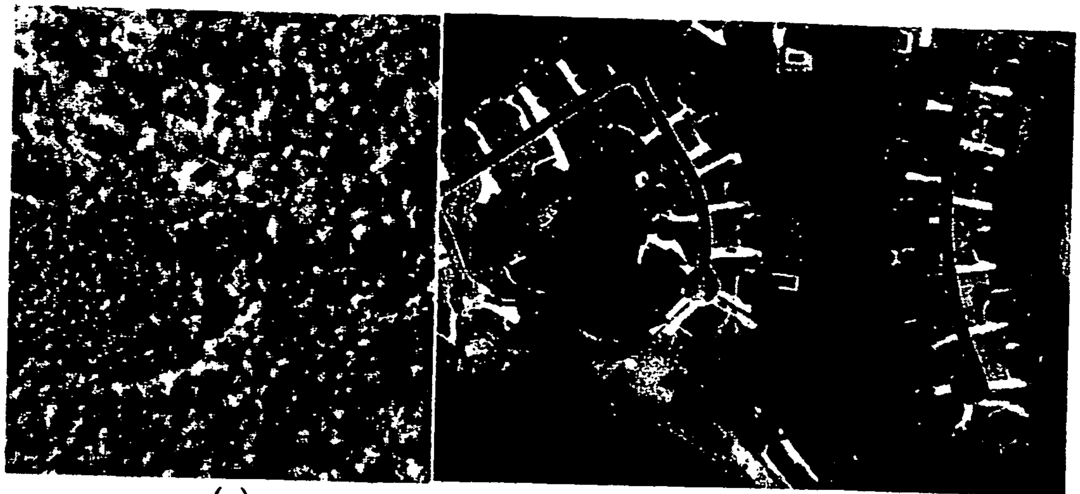
Figure 1: Satellite images of (a) mountain (b) mixed area.

Figure 3 shows the precesion versus recall for a given benchmark image before and after the S-STIR algorithm is applied. In this case, the sample size is selected to be 256, the number of radial basis functions is chosen to be 20 (thus requiring the clustering function TSVQ to generate 20 clusters from 256 vectors), and the final feature vector space has 10 dimensions. The parameter h is set at 3.16 throughout the experiment [9]. It is quite apparent that S-STIR algorithm produced a significant improvement on the precision for a given recall, and vice versa. The improvement is bigger for larger recall (or smaller precision).

To observe the impact from the parameter λ, we vary λ from 0.2 to 0.8. Smaller λ implies less emphasis on J_{sp} and more emphasis on J_{se}, resulting in better class separability (See Eq. 5). This is evident from Fig. 4, as lower λ results in better precision versus recall curve.

Larger initial sample size is important to the S-STIR algorithm, as it requires a better *global view* of the entire database to determine the transformation. Figure 5 shows that the precision versus recall performance dramatically deteriorates as the sample size is reduced from 256 to 64. Sampling techniques of the space can be applied and may produce a better *training set* for the S-STIR algorithm. This, however, is beyond the scope of this paper.

The number of radial basis function, and thus the number of clusters needed to be generated from the TSVQ clustering algorithm, also has an impact on the performance. As shown in Fig. 6, a point is reached when



(a) (b)

Figure 2: Satellite images of (a) forests (b) suburbs.

additional clusters will only fragmented the feature space and do not really help to produce a good decomposition of the original vector space.

The additional bonus of using the nonlinear multi-dimensional scaling technique is the reduction of dimensionality [2]. As shown in Fig. 7, the number of dimensions that are required for clean separation between the desirable and undesirable results is less than 5. Consequently, the precision versus recall curve are space fairly closely with respect to each other when the final number of dimensions is varied from 5 to 15.

4 SUMMARY

Similarity measure has been one of the critical issues for successful content-based retrieval. Simple quadratic forms of distance is inadequate as it does not necessary correspond to perceived similarity nor is it adaptive to different applications.

In this paper, we propose an iterative refinement algorithm for content-based retrieval of images based on low-level features such as textures, color histograms, and shapes that can be describe by feature vectors. This technique

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure	DISCLOSURE SUBMITTED BY	
Signature of Witnesses Date 12/18/97	Inventor's Signature Date 12/18/97	Inventor's Signature Date
	Inventor's Signature Date 12/18/97	Inventor's Signature Date
Signature of Witnesses Date	Inventor's Signature Date 12/18/97	Inventor's Signature Date
	Inventor's Signature Date	Inventor's Signature Date

DEC 22 1997

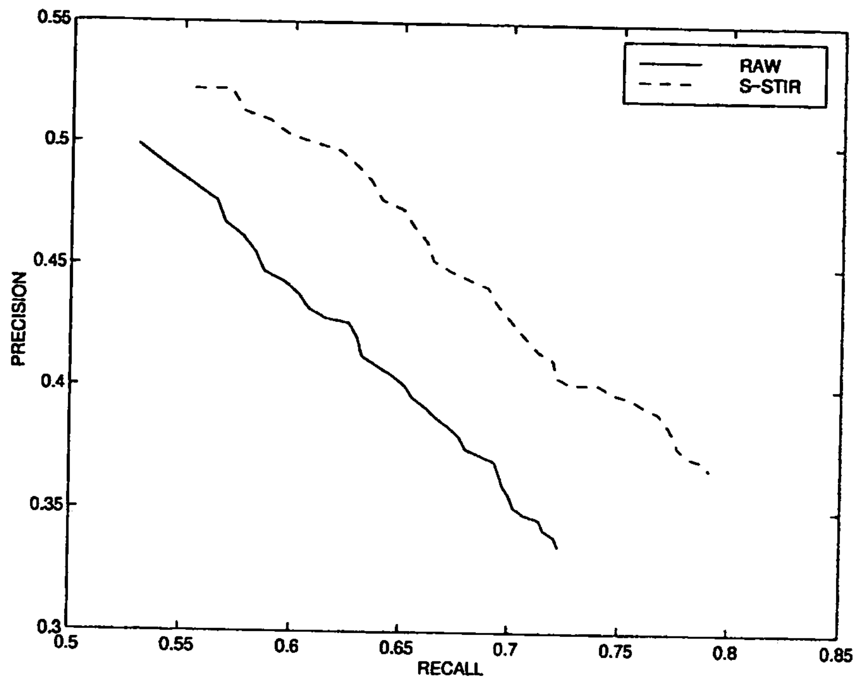


Figure 3: Comparison of precision versus recall for raw feature vector and feature vectors transformed by S-STIR algorithm.

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure		DISCLOSURE SUBMITTED BY			
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
	12/18/97		12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date
			12/18/97		
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
			12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date

97 DEC 22 AM 11:13

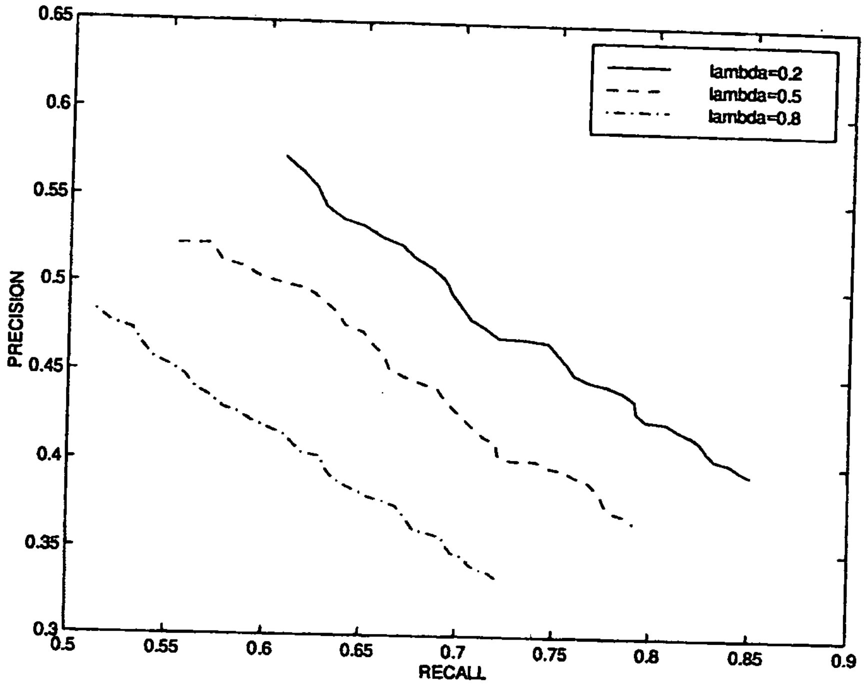


Figure 4: Effect on the precision versus recall for different values of λ.

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure		DISCLOSURE SUBMITTED BY			
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
	12/16/97		12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date
			12/18/97		
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
			12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date

97 DEC 22 AM 11:

Disclosure number ______________

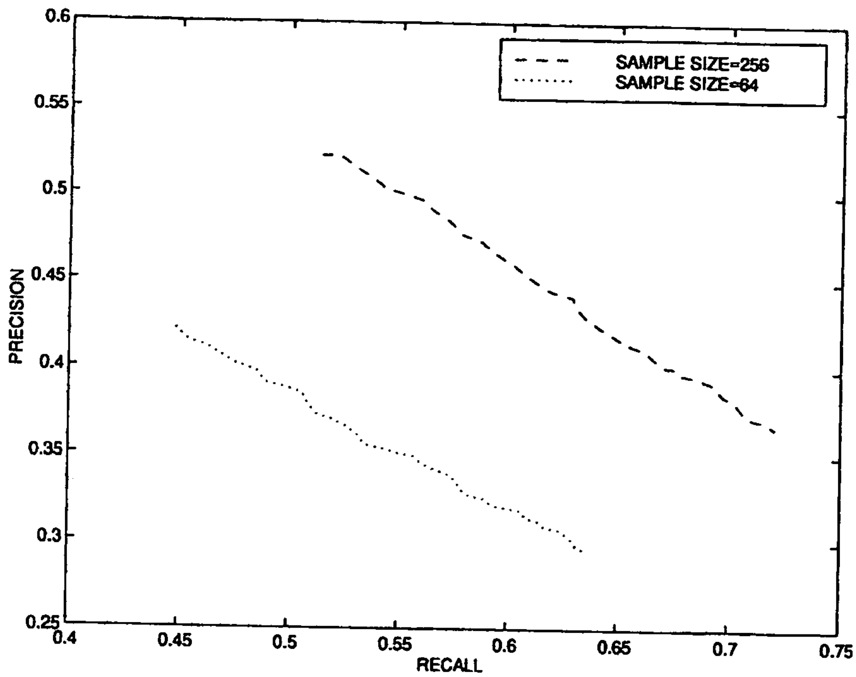


Figure 5: Effect on the precision versus recall for different values of sample size.

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure		DISCLOSURE SUBMITTED BY			
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
	12/18/97		12/18/97		
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
			12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date
			12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date

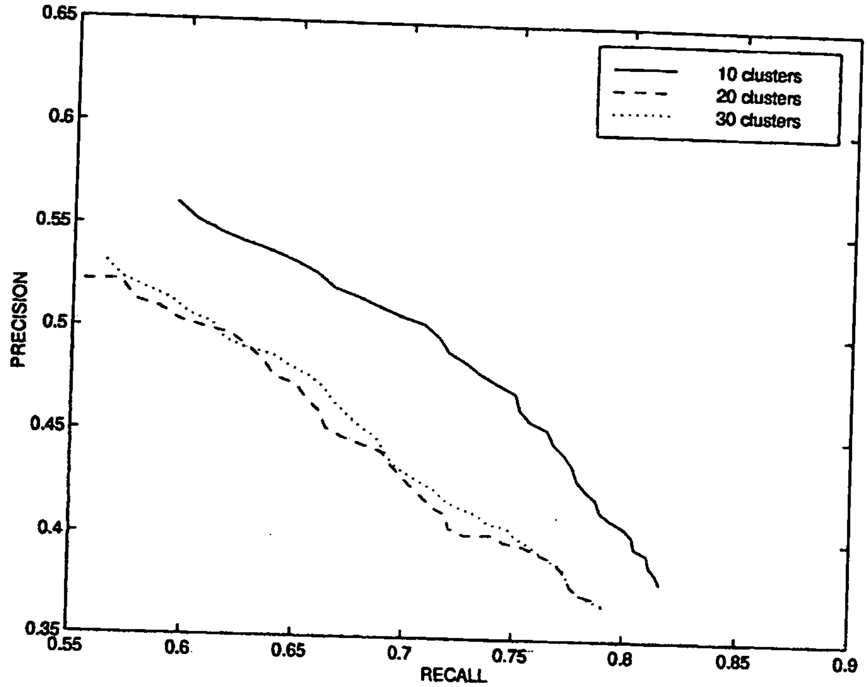


Figure 6: Effect on the precision versus recall for different number of clusters.

'97 DEC 22 A11:12

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure

Signature of Witnesses	Date
	12/18/97

DISCLOSURE SUBMITTED BY

Inventor's Signature	Date	Inventor's Signature	Date
	12/18/97		
	12/18/97		
	12/18/97		

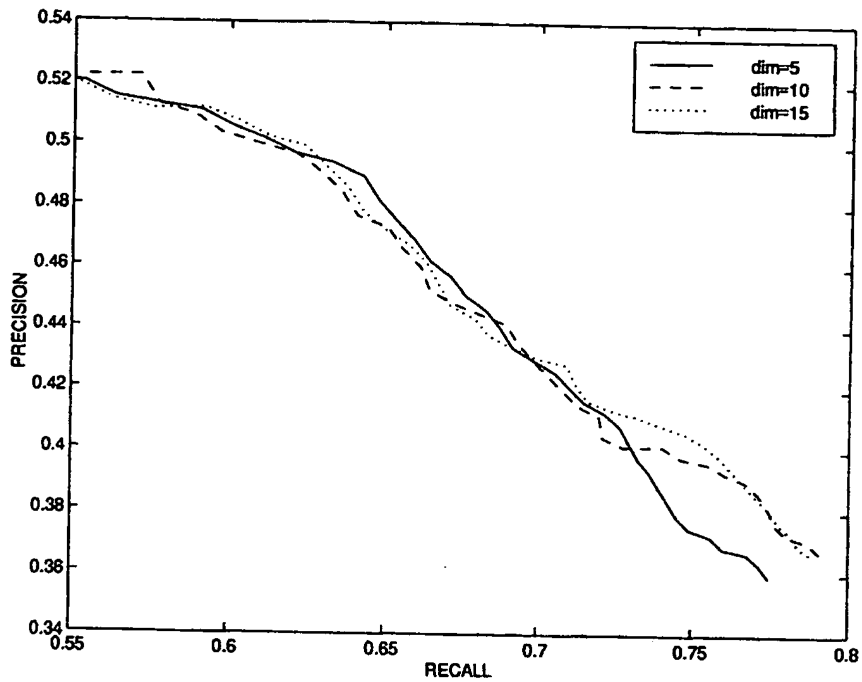


Figure 7: Effect on the precision versus recall for different values of final dimensionality.

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure		DISCLOSURE SUBMITTED BY			
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
	12/18/97		12/18/97		
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
			12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date
			12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date

adjusts the original feature space to the new application by performing nonlinear multidimensional scaling. Consequently, the transformed distance of those feature vectors which are considered to be similar is minimized in the new feature space. Meanwhile, the distance among clusters are maintained.

The major concern of using MDS for iterative refinement is that it will interfere with multidimensional indexing techniques such as R-tree. Existing R-tree indices are all pre-extracted and cannot dynamically adapt to the *warped* feature space each time a user make some labeling of the retrieved results. Consequently, efficient retrieval feature vectors from a large database becomes a serious issue again.

References

[1] J. R. Bach, C. Fuller, A. Gupta, A. Hampapur, B. Horowitz, R. Humphrey, R. C. Jain, and C. Shu. Virage image search engine: an open framework for image management. In *Symposium on Electronic Imaging: Science and Technology – Storage & Retrieval for Image and Video Databases IV*, volume 2670, pages 76 – 87. IS&T/SPIE, 1996.

[2] M. Beatty and B. S. Manjunath. Dimensionality reduction using multidimensional scaling for image search. In *Proc. IEEE International Conference on Image Processing*, October 1997.

[3] I. J. Cox, M. L. Miller, S. M. Omohundro, and P. N. Yianilos. Pichunter: Bayesian relevance feedback for image retrieval. In *Proceeding of the International Conference on Pattern Recognition*, pages 361 – 369. IEEE, 1996.

[4] M. Flickner, H. Sawhney, W. Niblack, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafner, D. Lee, D. Petkovic, D. Steele, and P. Yanker. Query by image and video content: The QBIC system. *IEEE Computer*, 28(9):23 – 32, September 1995.

[5] C.-S. Li, V. Castelli, and L. Bergman. Progressive content-based retrieval from distributed image/video databases. In *Proceeding of the International Symposium of Circuit and System*. IEEE, 1997.

[6] B. S. Manjunath and W. Y. Ma. Texture features for browsing and retrieval of image data. *IEEE Trans. Pattern Analysis Machine Intell. Special Issue on Digital Libraries*, (8), 1996.

[7] A. Pentland, R. W. Picard, and S. Sclaroff. Photobook: Tools for content-based manipulation of image databases. In *Proceedings of the SPIE Storage and Retrieval Image and Video Databases II*, February 1994.

[8] J. R. Smith and S.-F. Chang. Visualseek: A fully automated content-based image query system. In *Proc. International Conference on Image Processing*, 1996.

97 DEC 22

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure		DISCLOSURE SUBMITTED BY			
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
	12/18/97		12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date
			12/18/97		
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
			12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date

Disclosure number ____________

[9] A. R. Webb. Multidimensional scaling by iterative majorization using radial basis functions. *Pattern Recognition*, 28:753–759, 1995.

Alternatives

Potential Use

Potential applications include:

1. *Environmental epidemiology*: retrieve locations of houses which are vulnerable to epidemic diseases such as Hantavirus and Denge fever based on a combination of environmental factors (e.g. isolated houses that are near bushes or wetlands), and weather patterns (e.g. a wet summer followed by a dry summer).
2. *Precision farming*: retrieve locations of cauliflower crop developments that are exposed to clubroot, which is a soil-borne disease that infects cauliflower crop. Cauliflower and clubroot are recognized spectral signature, and exposure results from their spatial and temporal proximity.
3. *Medical image diagnosis*: retrieve all MRI images of brains that have tumors located within the hypothalamus. The tumors are characterized by shape and texture, and the hypothalamus is characterized by shape and spatial location within the brain.
4. *Real estate marketing*: retrieve all houses that are near a lake (color and texture), have a wooded yard (texture) and are within 100 miles of skiing (mountains are also given by texture).
5. *Interior design*: retrieve all images of patterned carpets which consist of a specific spatial arrangement of color and texture primitives.

WITNESSES: The two witnesses whose signatures appear below have read and understand this entire invention disclosure		DISCLOSURE SUBMITTED BY			
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
[signature]	12/18/97	[signature]	12/18/97		
Signature of Witnesses	Date	Inventor's Signature	Date	Inventor's Signature	Date
[signature]		[signature]	12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date
		[signature]	12/18/97		
		Inventor's Signature	Date	Inventor's Signature	Date

97 DEC 22 AM 11:13